Optimization of the Deposition Condition for Improving the Ti Film Resistance of DRAM Products

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Abstract. Dynamic random access memory (DRAM) products are the key parts in consumer products. To fulfill the current market's strict specifications, various customers have asked DRAM manufacturers to continue improving the quality of DRAM products. The resistance of the Ti film directly affects the electrical quality of DRAM products. At present, the DRAM products developed by the case company have caused customer returns due to abnormal resistance value of Ti film. Process engineers always adjust the engineering parameters based on experience, which resulted in slow improvement and inability to determine the setting of engineering parameters. Consequently, shipments of DRAM products are delayed. This study adopts the Ti film resistance of DRAM products as the main research object for improvement and applies the response surface method, neural networks, and genetic algorithms to help process engineers analyze and improve DRAM products. This work assists the case company in achieving a significant improvement in Ti film resistance from 210.33 Ω (the origin made by the case company) to 185.28 Ω (the improvement made by this work) where the specified target value is 185 Ω. The results are effective in shortening the improvement time and reducing customer returns.

Keywords: DRAM · Response surface method · Neural networks · Genetic algorithms

1 Introduction

Dynamic random access memory (DRAM) is typically used for the data or program code needed by mobile computing devices, workstations, servers and more. Ti film resistance is an important quality characteristic for the yield of DRAM products. An ideal Ti film resistance target value is, e.g., 185 Ω. A case company makes effort to improve the process to tune the Ti film resistance to the target value. If the Ti film resistance of a DRAM product is more closed to the target value, the quality of the DRAM product is better. If Ti film resistance is far from the target value, the quality of DRAM products will be low as well as the yield.

This case study considers DRAM products developed by a semiconductor company in Taiwan. During production, the DRAM products had an electrical abnormality, which

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was caused by product defects. Figure 1 shows the defect items of the DRAM products. The Ti film resistance value is the primary defect of the DRAM products, and it accounts for 46.7% of the total number of defects. Figure 2 shows a cross section of a DRAM product. The upper layer is the subject Ti film. To achieve quality control, the case company measured the Ti film resistance at 22 positions on each wafer. The measured positions are shown in Fig. 3. Figure 4 illustrates the daily average of the Ti film resistance of DRAM products in the case company during Jun. 1, 2019 and Aug. 28, 2019, where the total average resistance is 210.33 Ω.

The Ti film resistance of DRAM products has different measurement data because of different settings of engineering parameters. With the increase in the complexity of the manufacturing process, multiple engineering parameters need to be considered simultaneously when improving the quality of DRAM products. Using the experience of process engineers to perform experiments in the improvement stage would consume time and delay the product shipment schedule. Given the limited recourse of the case company, the optimal setting of engineering parameters should be determined within a short time. However, the case company cannot conduct numerous experiments. Therefore, this study integrates the response surface method (RSM), neural network (NN), and genetic algorithm (GA) to improve the Ti film resistance of DRAM products to enhance the electrical quality of the products.

The paper is organized as follows. Section 2 refers to related literature presenting fractional factorial design, response surface method, artificial neural network and genetic algorithm. Section 3 outlines a proposed approach for improving DRAM products. Section 4 presents a case study, the proposed approach was used to improve the resistance of DRAM products. Section 5 summarizes our conclusions.

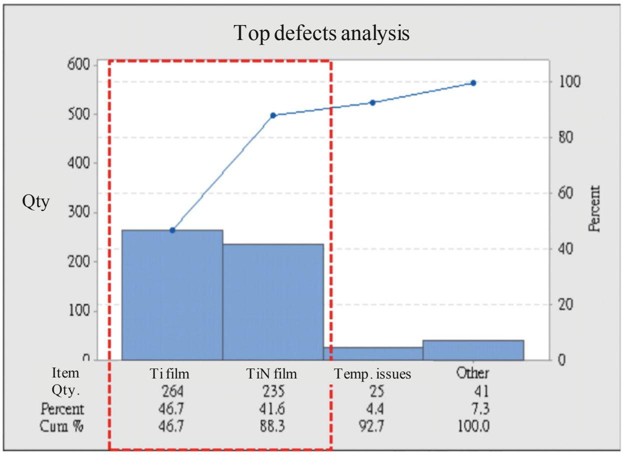

Fig. 1. The top defects in a DRAM product

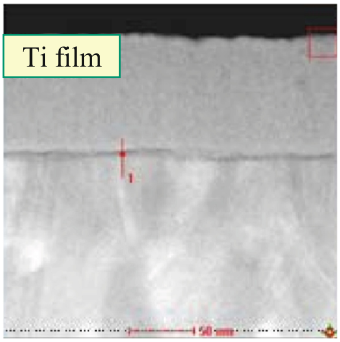

Fig. 2. The cross section of a DRAM product

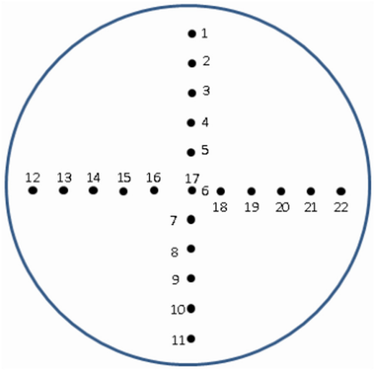

Fig. 3. The positions of the measured resistance for the quality control

2 Related Work

The design of experiment (DOE) methodology was developed to find the optimal engineering parameters in an experiment by Fisher in the early 19th century [1]. Full factorial design examines all of the engineering parameters in the experiment. As the number of engineering parameters increases, the number of examinations and cost in a full factorial design also increase. For example, for an experiment with seven 2-level parameters, 27 = 128 times of examinations should be performed to find the optimal engineering parameters. The cost is also exponential growth. To solve this problem, Box and Hunter proposed the fractional factorial design in 1961 [2]. Fractional factorial design is part of the full factorial design experiment. The engineering parameters that are similar to those of the full factorial design can be found but with the fewer number of examinations. The main idea of the fractional factorial design is to select the important engineering parameters with the major impact on the results of the experiment. If an experiment with seven 2-level parameters has 5 important engineering parameters, the number of examinations is reduced to 27–2 = 32 using the fractional factorial design. Therefore, the fractional factorial design has great help in selecting important engineering parameters and saving cost, and it has been widely used in various product and process improvement.

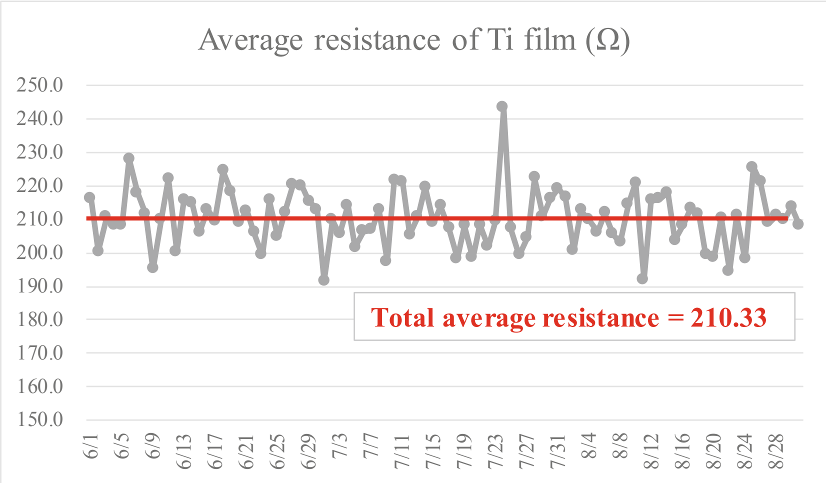

Fig. 4. The trend chart of average resistance of Ti film

Arévalo et al. (2019) established a fractional factorial design concluded in a total of 28 experiments to determine the critical variables values in which the matrix tablets reach the required quality [3]. Dias and Dias (2018) performed a fractional factorial design (24 − 1) to evaluate the contrasts of the dealumination variables (temperature, humidity, dealumination degree and washing) in each response (Si/Al ratio, number of acid sites, catalytic conversion) [4]. Harborne et al. (2018) used fractional factorial design for protein engineering to identify the most important residues involved in the interaction between AcrB and nickel resin [5].

Box and Wilson [6] proposed an experimental design method called response surface method (RSM) that provides a series of analysis steps to optimize the response of products, processes, and systems. RSM integrates a statistical regression model to predict the response value under different engineering parameters [7]. The principle is to construct the relationship between engineering parameters and response variables, and determines the optimal engineering parameters of the system. In practical applications, the RSM has been widely used in many enterprise improvement activities. Sharifi et al. (2018) applied a response surface methodology to determine the optimum synthesis parameters which are related to the paper sheets revealed that adding PANi decreases the amounts of breaking length, and tear and burst factors [8]. Tuzen et al. (2018) They adapted response surface methodology to combine both the high surface area and the active sites to enhance adsorption of the dye [9]. Most of practical applications used the second-order RSM model to construct the non-linear relationship of the input control factors and response variable. To further improvement, we try to use an artificial neural network to model the non-linear relationship of the input control factors and response variable in the paper.

The implementation of RSM generally requires at least two continuous engineering parameters to construct a response surface.

If $E[y] = E[f(x_1, x_2, \ldots x_n) + \varepsilon]$, where ε is the error observed in response value y, is used to present the expected response value, then the formed surfaces on E[y] under different combinations of x_1, x_2,…x_n are called response surface, and the point with the best response value usually has the largest curvature.

The response surface can be used to estimate the response value, determine the best setting of engineering parameters, and find the optimal solution value. For RSM, an appropriate mathematical relationship should be established between the engineering parameters and response variable, and this can be achieved by using low-order polynomials of engineering parameters in certain region, such as a first-order model. However, when the relationship in the system has curvature, it must be expressed by a higher-order polynomial, such as a second-order model [10].

If the response value can be obtained as a linear function, the function is a first-order model, as shown in the following formula.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon, \tag{1}$$

where β_0 represents the intercept of the response surface and $\beta_1, \beta_2, \ldots \beta_k$ is the coefficient of each control variable.

If the system requires a model with curvature to estimate the response value, then a second-order model must be used. In addition to the items of the first-order mode, the second-order mode has interaction term $x_i x_j$ and quadratic term x_i^2, as shown in the following formula.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum \sum_{i<j}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{2}$$

In RSM experimental design, a screen experiment (fractional factorial design) is initially used to select the important engineering parameters that affect the response value, and these important engineering parameters are utilized to construct the response surface. Then, a first-order response surface is established to determine whether the optimal solution falls within the current region of engineering parameters. To confirm that the experimental region already contains the optimal solution value, we can use the center-point experiment design and analysis of variance (ANOVA) to determine is the significance of curvature in this experimental region. If the curvature is significant, then the optimal solution value may be within this region, and we can continue to construct the second-order response surface to determine the optimal setting of engineering parameters. However, if the curvature is not significant, then the steepest path that can increase or decrease the response value should be identified from the current experimental region, and the path to the optimal solution value should be advanced. The most common search method is the method of steepest descent or ascent, which is used to find the new experimental region of engineering parameters that may contain the optimal solution; then, the second-order response surface is constructed to determine the optimal setting of engineering parameters.

3 The Proposed Approach

This study initially uses the fractional factorial experimental design to assist the case company in selecting important engineering parameters and then adopts the center-point experimental design to confirm the presence of curvature within the region of engineering parameters. When curvature exists in the region of engineering parameters, the RSM is used for modeling; when no curvature exists, the steepest descent method is required to determine the new experimental region that may contain the optimal solution. Afterward, RSM is implemented for the region of engineering parameters where the optimal solution may exist, and some applicable experimental data are collected by RSM experiment. Artificial neural network (ANN) is modeled with RSM experimental data to establish the relationship between each engineering parameter and Ti film resistance of DRAM products. Finally, genetic algorithm (GA) is used to find the global optimal setting of engineering parameters. After finding the optimal setting of engineering parameters, confirmation experiments are required to verify the effectiveness of the proposed approach. The flow of proposed approach is shown in Fig. 6.

ANN training involves adjusting the link value continuously [12, 13]. The link value is a kind of weight; the larger the value is, the more likely the connected neuron is to be excited (the more important it is to the output variable). When multiple neurons are combined, they can create an ANN. Figure 5 shows an ANN composed of three layers of neural-like units. The first layer is an input layer composed of input units (engineering parameters). These input units are initially connected to the nodes of the hidden layer and then connected to the output units of the output layer through adjustable weights. Afterward, each output unit corresponds to a specific engineering feature.

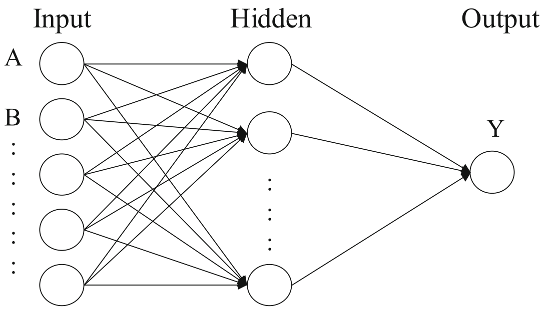

Fig. 5. Structure of ANN

ANN must be trained repeatedly so that each input engineering parameter can correctly correspond to the required output variable. Before ANN training, a training dataset must be prepared to offer a reference template for the network in the learning process. The purpose of ANN training is to make the output value of ANN close to the target value so that the error between the two becomes increasingly small [14]. When the error between the two hardly changes, the ANN has reached convergence and completed training. When the neural network is trained through the training samples, although the output of the neural network is close to the required value, we do not know what output results will be obtained for inputs that are not generated by the training samples. Therefore, another set of untrained samples must be used for the neural network to confirm the error between the predicted value and the known feature value. This sample is called the testing dataset.

The learning rate is a crucial parameter in an ANN training. The learning rate affects the convergence speed of ANN. If the learning rate is large, then the convergence of ANN will become fast. Conversely, a small learning rate makes the convergence of ANN slow. Fausett [15] and Hagan et al. [16] demonstrated the process of selecting appropriate ANN parameters.

Recent studies have used neural networks to elucidate the ability to learn the complex relationships between the engineering parameters and response variable, usually for process and quality control. Wang et al. (2019) used a two-layer neural network and genetic algorithm to established a fast approach to cavitation optimization and a parametric database for both hub and shroud blade angles for double suction centrifugal pump optimization design [17]. Mukherjee and Rajanikanth (2019) applied an artificial neural network to predict the variation of nitric oxide/nitrogen dioxide when the exhaust is subjected to discharge plasma [18]. Hu et al. (2019) developed an artificial neural network to predict polarization curves under different complex sea environments [19].

GA simulates the natural selection rule of the biological world, the natural elimination rule of the fittest, leaving only ethnic groups that best meet the living conditions. GA differs from conventional search techniques that conduct a point-to-point search in the solution space. GA is a robust adaptive-optimization technique that allows an efficient probabilistic search in high-dimensional space [20]. Many experts and scholars have invested in further exploration and research on the evolution of GA and confirmed the feasibility of this algorithm. Hosseinabadi et al. (2019) investigated genetic algorithms for solving Open-shop scheduling problem (OSSP), which could generate better solutions compared to other developed algorithms in terms of objective values [21]. Alipour-Sarabi et al. (2019) used genetic algorithm to minimize total harmonic distortion of the output signals, and consequently the estimated position error in concentrated coil wound field resolvers [22].

GA treats each engineering parameters in the engineering problem as a biological gene, transforms each variable in a binary encoding, and combines them into chromosomes. Each chromosome represents an independent population. GA generates the first generation in a random manner as the initial condition of the algorithm search, and each generation has multiple independent populations. The objective function of the engineering problem is then converted into a fitness function. The higher the fitness function value of population is, the stronger its adaptive capacity is and the greater the probability of producing offspring is. The evolution process of GA includes three major steps, namely, reproduction, crossover, and mutation of chromosomes. The evolution process occurs in the solution space of the engineering problem until the most adaptive solution (the optimal solution) that meets all the constraints is obtained. The chromosome with the highest fitness function value is determined after multiple generations of reproduction (multiple iterations). This chromosome is the global optimal solution we wish to find [23].

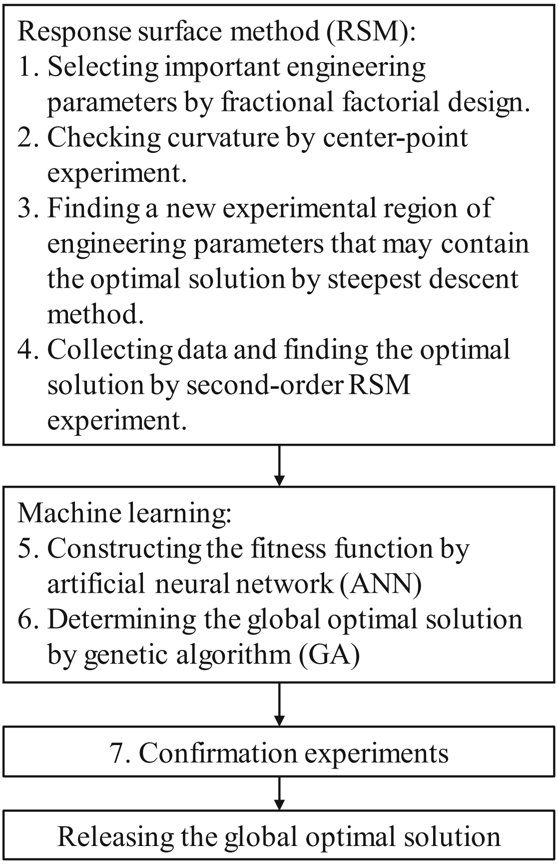

Fig. 6. Proposed approach

4 Case Study

The manufacturing process that affects the Ti film resistance in DRAM products includes five main processes, namely, via etch, Ti deposition, structure film deposition, CMP, and etching, as shown in Fig. 7. Six engineering parameters were selected based on the practical experience of process engineers; these six engineering parameters were AC bias power, backside Ar flow, backside pressure, heater temperature, E-chuck voltage, and composition time. The levels of the engineering parameters are shown in Table 1, where Level (+1) represents a high level and Level (−1) represents a low level. Through a fractional factorial design, 2^{6-2} DOE was selected as a screen experiment for selecting important engineering parameters. The engineering parameters (A–F) are arranged in the 2^{6-2} DOE.

The experimental results of 2^{6-2} are shown in Table 2. The factor response table, factor response chart, and ANOVA results of the resistance analysis results are presented in Table 3, Fig. 8, and Table 4, respectively. Table 3 shows that the contribution of each engineering parameter from high to low is E(21.62) > A(8.76) > D(6.32) > F(2.40)

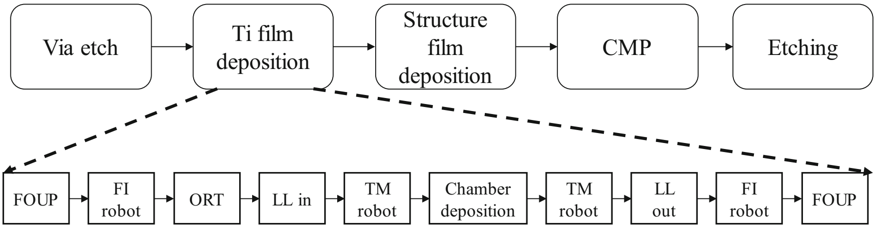

Fig. 7. The manufacturing process of the Ti film of DRAM products

Table 1. Engineering parameters and their levels for the fractional factorial design

Factor	Ac bias power (W)	Backside Ar flow (sccm)	Backside pressure (mTorr)	Heater temperature (°C)	E-chuck voltage (V)	Deposition time (sec)
	A	B	C	D	E	F
Level (s−1)	350	2	4000	250	285	3
Level (+1)	450	6	6000	260	385	5

> C(0.64) > B (0.35). Table 4 shows that the p-value of engineering parameters B, C, and F on Ti film resistance was not significant and can be ignored. In Fig. 8, a better combination of the engineering parameters could be set at A = 350 W, D = 250 °C and E = 300 V. In the next step, three important engineering parameters, namely, A (AC bias power), D (heat temperature), and E (E-chuck voltage), were used to design the center-point experiment for confirming whether the experimental region of engineering parameters contains curvature, that is, whether the experimental region contains the global optimal solution.

Due to check the better combination of the engineering parameters in previous factorial experimental design (A = 350 W, D = 250 °C and E = 285 V). We re-arranged a center-point experiment that contained full factorial experimental design and performed experiments with center points. Through full factorial design, 2^3 DOE is selected as the experimental arrangement for this step. Then, engineering parameters A, D, and E are arranged in the 2^3 DOE, and five center points are planned.

Through the first-order mode (e.g., Formula (1)), response value also changes when the level of engineering parameters changes. Each effect of engineering parameters depends on its main effect coefficient, that is, $\beta_1, \beta_2, \ldots \beta_k$. To reduce the response value effectively, we must find the direction that decreases response value the fastest and proceed toward this path. This path is called the path of steepest descent. The procedure of the sequential movement refers to the experiment in existing experiments of first-order model, which is performed along the steepest descent path until the response value no longer increases. The results of successive experiments can confirm that the optimal point has been reached. If it has already been reached, the more accurate second-order model is needed to obtain the optimal solution.

Table 2. The 2^{6-1} array and data for the fractional factorial design experiment

EXP	Engineering parameters						Resistance (Ω)
	A	B	C	D	E	F	
1	−1	−1	−1	−1	−1	−1	176.56
2	1	−1	−1	−1	−1	1	190.71
3	−1	1	−1	−1	−1	1	176.61
4	1	1	−1	−1	−1	−1	189.92
5	−1	−1	1	−1	−1	1	182.63
6	1	−1	1	−1	−1	−1	187.83
7	−1	1	1	−1	−1	−1	187.22
8	1	1	1	−1	−1	1	185.99
9	−1	−1	−1	1	−1	1	182.69
10	1	−1	−1	1	−1	−1	200.07
11	−1	1	−1	1	−1	−1	183.10
12	1	1	−1	1	−1	1	198.77
13	−1	−1	1	1	−1	−1	189.00
14	1	−1	1	1	−1	1	190.56
15	−1	1	1	1	−1	1	191.36
16	1	1	1	1	−1	−1	197.73
17	−1	−1	−1	−1	1	1	205.97
18	1	−1	−1	−1	1	−1	212.90
19	−1	1	−1	−1	1	−1	200.35
20	1	1	−1	−1	1	1	211.85
21	−1	−1	1	−1	1	−1	199.79
22	1	−1	1	−1	1	1	206.40
23	−1	1	1	−1	1	1	201.85
24	1	1	1	−1	1	−1	216.53
25	−1	−1	−1	1	1	−1	213.42
26	1	−1	−1	1	1	1	213.90
27	−1	1	−1	1	1	1	205.04
28	1	1	−1	1	1	−1	216.76
29	−1	−1	1	1	1	1	207.37
30	1	−1	1	1	1	−1	221.09
31	−1	1	1	1	1	−1	210.63
32	1	1	1	1	1	1	212.80

Table 3. Factor response table of average resistance of Ti film for the fractional factorial design experiment

Level	A	B	C	D	E	F
Level (−1)	194.60	198.81	198.66	195.82	188.17	200.18
Level (+1)	203.36	199.16	199.30	202.14	209.79	197.78
Effect	8.76	0.35	0.64	6.32	21.62	2.40
Rank	2	6	5	3	1	4

Using the regressed equation in ANOVA Table, the first-order model as follows:

$$\text{Resistance} = 200.068 + 4.08\,\text{A} + 3.41\,\text{D} + 11.09\,\text{E}. \tag{3}$$

Then, the steepest descent method is used to make the response estimate move forward along the steepest descent path from the current center point (A = 0, D = 0, E = 0) to obtain the optimal response value. The moving direction is determined by the maximum value of the main effect coefficient because it makes the response value move toward the optimal value at the highest speed. In the first-order model of this study, the coefficient value of parameter E is 11.09, which is larger than the coefficients 4.08 of A and 3.41 of D, indicating that parameter E is the main variable of the steepest descent path. The experiment was executed, and the Ti film resistance obtained on this path was measured until it increased progressively.

Figure 9 presents surface plot of the thickness variation for the second-order model of RSM. The p values of RSM are all smaller than 0.05, which confirms the significance in the second-order model experiment.

The first-order items (A, D, and E) and second-order items (A^2, D^2, and E^2) are significant engineering parameters. Simultaneously, Factor A is related to A^2, factor B is related to B^2, and factor C is related to C^2. Therefore, A^2, D^2, and E^2 were adopted as input variables for the neural network. The difference between the Ti film resistance and the specified target value (185 Ω) was taken as the output variable (the smaller is better).

$$\text{Resistance} = 8161 - 6.33\,\text{A} - 52.4\,\text{D} - 6.75\,\text{E} + 0.01029\,\text{A} * \text{A} + 0.1079\text{D} * \text{D} + 0.01779\,\text{E} * \text{E}. \tag{4}$$

First, 80% of the data were randomly selected from the data set as the training dataset for ANN. The other 20% of the data were used as the training dataset for the network. The learning and momentum rates were set to 0.1 and 0.85, respectively. To determine the number of nodes in the hidden layer, this study performed 1,000 modeling iterations with neural structures, such as different numbers of nodes. Then, the ANN architecture of 3-6-1 is used for modeling as shown in Fig. 10.

To confirm the optimal setting of the engineering parameters, we used a total of five lots in this study, and five wafers were obtained from each lot for confirmation experiments. The experimental measurement data are shown in Table 5. According to the confirmation experiment, average resistance = 185.28 Ω is very close to the

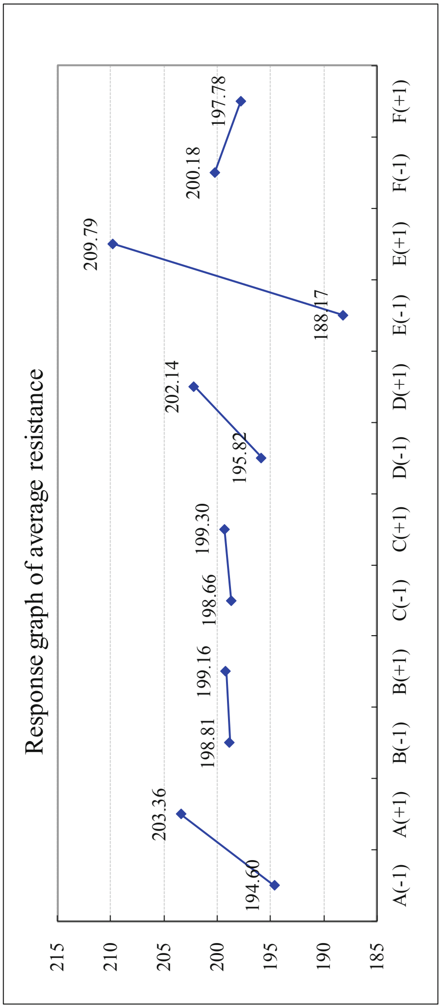

Fig. 8. Response graph of average resistance of Ti film for the fractional factorial design experiment

Table 4. The ANOVA of the resistance of Ti film

Source	DF	SS	MS	F-Value	P-Value
A	1	614.43	614.43	46.61	0
B	1	0.99	0.99	0.07	0.787
C	1	3.23	3.23	0.24	0.625
D	1	319.92	319.92	24.27	0
E	1	3738.96	3738.96	283.64	0
F	1	46.08	46.08	3.5	0.073
Error	25	329.55	13.18		
Total	31	5053.15			
				R-Sq	R-Sq(adj)
				93.48%	91.91%

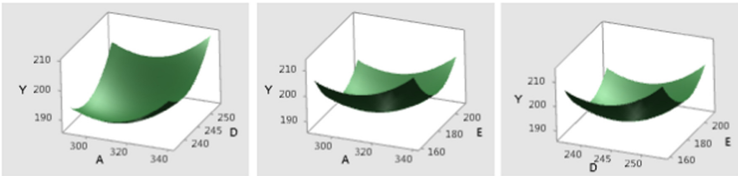

Fig. 9. The surface plot of resistance for the second-order model experiment

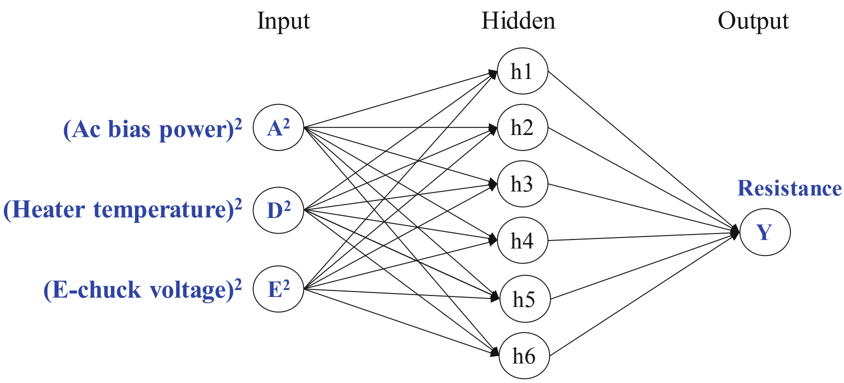

Fig. 10. The neural network structure of the Ti film production process

improvement target 185 Ω. Hence, we confirmed that the global optimal setting of engineering parameters is a feasible combination.

After the DRAM products of the case company were further improved by the artificial neural network and genetic algorithm, we found that the resistance improved significantly. The average resistance of the Ti film improved by 98.88% from 210.33 Ω to 185.28 Ω, as shown in Table 6.

Table 5. Confirmation experiments for the genetic algorithm

EXP	Resistance					Average resistance (Ω)
	Wafer #1	Wafer #2	Wafer #3	Wafer #4	Wafer #5	
Lot #1	184.97	184.80	184.81	186.14	185.52	185.25
Lot #2	185.23	185.09	185.67	184.80	185.94	185.35
Lot #3	185.23	185.92	185.63	185.76	185.09	185.53
Lot #4	185.12	185.75	184.25	185.25	184.99	185.07
Lot #5	185.05	185.20	185.07	184.75	186.05	185.22
						185.28

Table 6. Comparison between the initial data and the proposed approach

Comparison	Ac bias power (W)	Heater temperature (°C)	E-chuck voltage (V)	Average resistance (Ω)	Resistance difference(Ω)
	A	D	E		
Before improvement	450	260	400	210.33	25.33
RSM	307.6	242.8	189.7	187.66	2.66
NN & GA	292.2	240.5	212.8	185.28	0.28
Improvement					98.88%

5 Conclusions

The case company always accrues high experimental costs due to trial and error and has not effectively improved the Ti film resistance of DRAM products. Therefore, in this study, several important engineering parameters that affect the Ti film were identified through fractional factorial experiments. Three important engineering parameters (i.e., AC bias power, heat temperature, and E-chuck voltage) were determined in ANOVA table. A center-point experiment was conducted, and the steepest descent method was used to find the possible experimental region of engineering parameters containing the optimal solution that falls around AC bias power = 313.2 W, hat temperature = 246.9 °C, and E-chuck voltage = 200 V. For the second-order model experiment, the RSM experiment design was implemented according to the above experimental region that may include the optimal value. The RSM experiment obtained the optimal setting of engineering parameters of the second-order model, that is, AC bias power = 307.6 W, heat temperature = 242.8 °C, and E-chuck voltage = 189.7 V. After verifying the optimal factor setting of this second-order model, the average resistance was reduced from 210.33 Ω to 187.66 Ω, with an improvement of 89.5%. In addition, ANOVA of the RSM experiment showed that the second order items of the second-order model (AC bias power)^2, (heat temperature)^2, and (E-chuck voltage)^2 had significant effect on the response values. ANN used the three second order items as the input variables to construct a 3-6-1 neural network. Then, the global optimal setting of engineering parameters found by the genetic algorithm was AC bias power = 292.2 W, heat temperature = 240.5 °C, and E-chuck voltage = 212.8 V. The average resistance improved from 210.33 Ω to 185.28 Ω, with an improvement of 98.88%. To release to the global optimal setting of engineering parameters, the case company will conduct mass production stage to verify the feasibility of the global optimal setting in the future.

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